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An efficient method for electric meter readings automatic location and recognition

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Abstract

An efficient and robust meter readings location and recognition algorithm plays a very important role in remote meter reading systems and automatic meter inspection systems. A novel and efficient electric meter readings automatic location and recognition method is presented in this study. It includes the following three steps: coarse-to-fine detection of meter readings, projection-based character segmentation and BP neural network recognition. The algorithm was tested on HUALI, KEYUAN, JINLING, LANJIER and SANXING electric meter images. Experimental results show that the proposed method has satisfying performance and good robustness.

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Keywords: Electric Meter Readings; Coarse-to-fine Detection; Character Segmentation; BP Neural Network

1. Introduction

There are more than three thousand lisenced electric meter production enterprises in China. Different manufacturer has their own design, as shown in figure 1. And these different electric meters are using in different cities, because of the standard hysteresis and local protectionism. Hence the development of remote meter reading systems and automatic meter inspection systems in China is difficult. Electric power companies have to pay a lot of money for artificial meter reading. Simultaneously, the accuracy and real time measurement cannot be satisfied.

Most existing electric meter readings location and recognition researches are focus on one 'type' of products[1],[2]. The robustness is not satisfied. On the other hand, the type-based methods may not work properly when the image contains abnormal illumination or high frequency noise.

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Electric meter readings location and recognition system can be divided into three parts, meter readings detection module, reading character segmentation and optical character recognition. An accurate detection method, which eliminates the disturbance of image distortion, merged characters and borders, is the foundation of the system. Segmenting the characters accurately is the guarantee of the recognition rate improvement. Finally, designing or choosing a proper character recognition method occupies the dominant position in the system.

The rest of this paper is organized as follows: In the next section, we describe the meter readings detection module, named coarse-to-fine detection method. In section 3, characters segmentation algorithm is introduced and the dominant optical character recognition method is given in section 4. Experiments on several types of electric meter readings images are presented in section 5. Finally, we draw some conclusions in section 6.

a) HuaLi b) JinLing c) KeYuan

d) LanJier e) SanXing

Fig. 1. Electric meters by different manufacturer

2. Coarse-to-fine Detection of Meter Readings

In order to recognize the electric meter readings automaticly, we have to detect the readings' location from the whole image. In other word, we want to find the region of interest (ROI). Firstly, projection in color space is conducted for the coarse detection. Then the coarse area is divided into the integral number region and decimal part. Finally, the ROI is detected using the projection of the histogram.

2.1. Coarse detection

Electric meter readings coarse detection is going to detect start and end position along the y-axis. Firstly we define a specified color as the ROI_color according to different types of eletric meters. It is a weighted norm in the RGB space, and defined to be:

$$ROI\_color = a_1 R + a_2 G + a_3 B \tag{1}$$

where R, G and B are the three chanel of the color space and $\sum_{i=1}^{3} a_i = 1$. For example, the feature of HuaLi meter's ROI is blue value. Hence we can define its ROI-color as $ROI\_color = 0.05R + 0.05G + 0.9B$. Then the orthogonal projection is conducted,

$$\mathrm{Pr}\,oj_i = \sum_{j=1}^{W} ROI\_color(i,j), \quad \mathrm{i} \in [1,H] \qquad (2)$$

where W and H are the width and height of the image respectively. From the result of the orthogonal projection, we can find some peak and trough. And these help us determine the coarse location of the meter readings. For example, Figure 2 is the projection result of HuanLi meter based on its ROI_color. From the first peak of this projection, we can find out the start and end position of the HuaLi meter along the y-axis. They are $y\_start = 51$ and $y\_end = 106$.

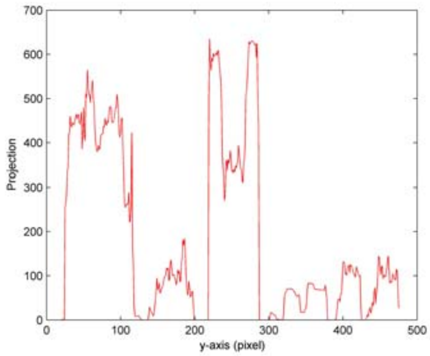

Fig. 2. Orthogonal Projection of HuaLi meter based on the ROI_color

Using the start and end position information, the coarse location of meter readings can be detected. Figure 3 shows the coarse detection result of the HuaLi meter.

Fig. 3. Coarse detection of HuaLi meter

2.2. Final detection

The readings include several integral numbers and one decimal number, as shown in figure 3. We have to disconnect the two parts. As a production standard, the background color of the decimal frame is different with the integral one. For example, the background color of the HUALI meter's decimal frame is red while its integral frame's background color is black. Based on this information, we know that horizontal projection can be used. As the process of horizontal projection is similar to the orthogonal one which is described in the previous section, we omit the detailed discussion here and refer the readers to Ref. 3.

Coarse detection result just gives us the start and end position along the y-axis. Besides the readings, the result image(figure 3) contains useless information, such as the left and right region. The histogram projection of the black&white image of the coarse detection result is used to conduct the final detection. The specific practices are as follows. To detect the left correct position, column scan is conducted from left to right, until the middle positon of the image is reached. The number of white pixels in each column is counted, and defined as $Count\_i$. If $Count\_i > 1$, the index of this column is recorded as i_begin. The column scan is continued. While $Count\_i < 1$ first appear after the i_begin is recorded, we record this column's index as i_end. If

$$i\_end - i\_begin \geq 0.8 \times w \tag{3}$$

is satisfied where w is the width of the character, i_begin is updated using i_end. If there exist one column whose number of white pixels satisfy $Count\_i \geq 0.8 \times h$, where h is the height of the character, then the newest i_begin is the left margin we want. According to this process, the right margin of the readings can be determined. Figure 4 gives the final detection result of the HUALI meter. It is a binary image.

Fig. 4. Final detection of HuaLi meter

3. Character Segmentation

Character segmentation has long been a critical area of the OCR process[4]. It is to segment each character from the whole image. Accurate segmentation is the guarantee of the recognition rate improvement.

Different with the complicated methods introduced in [4], we still employ the usefull projection scheme, for the simplicity of the system and the high quality of the captured images. The binary image is scaned column by column. And the number of white pixels is counted. The gradient of the amount of white pixels is computed for each column. While its value is higher than the threshold($0.2h$ in our experiments), the segmentation margin is obtaind. Figure 5 shows the segmentation result from the final detection image (figure 4).

Fig. 5. Segmentation result of the five characters

4. Recognition of Electric Meter Readings

Electric meter characters, similar to car license plate characters, are inerratic relatively. As we kown, BP neural networks is widely used for recognizing car license plate characters and has satisfied performance[5]. BP nerual networks is a form of multiprocessor computer system with multiple advantages, such as simple processing elements, a high degree of interconnection, simple scalar messages and adaptive interaction between elements. However, the flaws and shortcoming of BP neural network are obvious. Firstly, all learting rate weights of BP neural network are the same and all weights vary with a same learning rate. Secondly, convergence value of BP neural network is not always the global minimum value of the error function. Because of these flaws, parameter setting and structural design of BP neural network are the key steps when applying to electric meter readings recognition.

4.1. Neural network strutrual design

Kolmogorov's theorem shows us that any continuous real-valued function $f: U^n \to R^m, f(X) = Y$ defined on [0, 1] can be represented in the form $f = \sum_{i=1}^{2n+1} g_i(\sum_{j=1}^{n} \varphi_{ij}(x_j))$, where the $g_i, (i = 1 \cdots 2n+1)$ is properly chosen continuous function of one variable[6]. The network architecture of Figure 6 captures the basic idea of Kolmogorov's theorem. The theorem implicates that the function approximation ability of neural networks depending on its number of neurons in hidden layer. Single hidden layer neural networks are universal approximators. Electric meter readings recognition belongs to small-category classification problems, hence single hidden layer neural network is enough for this recognition problem. The network is formed in three layers, called the input layer, hidden layer, and output layer.

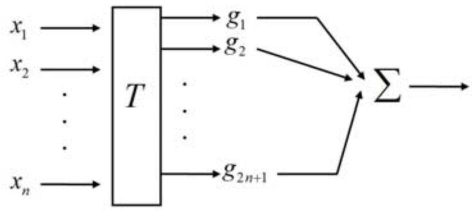

Fig. 6. Kolmogorov's theorem

There are several separate steps when applying neural network approach to recognize electric meter readings. The first step is to translate the binary character data into a friendlier form. We select 35 pixel grid features from the segmentation result image for recognition. Hence the number of the input neurons is determined based on the dimension of feature vectors.

The number of neurons in the output layer is determinded based on the category number of objects to identify. Obviously, the number of the output layer nodes should be 10 because there are only 10 feasible recognizing objects in the electric meter readings. And their desired output is easy to determinded. For example, the desired output of digital 1 is (1,0,0,0,0,0,0,0,0,0) while digital 2 is (0,1,0,0,0,0,0,0,0,0).

The selection of the number of hidden-layer nodes is another important aspect. Local minimum and slower convergence speed are the two contradictory aspects while the number of hidden-layer nodes is too small or too big. An empirical formula for initially selecting the number of hidden nodes is introduced as follows by Hirose et al., based on many applications in various fields[7].

$$h = 0.51 + \sqrt{0.43mn + 0.12n^2 + 2.54m + 0.77n + 0.35} \tag{4}$$

where h is the number of neurons in the hidden-layer, m is the number of input neurons 35, and n is chosen to be the number of the output layer nodes 10.

4.2. Neural network parameters

The parameters control the neural network computations, such as the selection of activation transfer functions, learning rate and maximum total error.

As mensioned before, electric meter readings recognition is a small-category classification problem. Hence sigmoid function and linear function can be selected as activation transfer functions of the hidden layer and output layer respectively.

Learning rate of a neural network determines the weights variation generated in each training process. Big learning rate can lead to system unstable while small one brings about slow convergence. Generally, the correct setting for the learning rate is application-dependent. The learning rate of the electric meter readings recognition system is determined to be 0.02 based on a number of experiments, which has a stable guarantee and reach a fast convergence speed.

Maximum total error is related to the number of neurons in the hidden-layer. We trained several networks with different maximum total error. Several factors, such as computational time, the number of hidden-layer nodes and recognition testing results were concerned. And at last an appropriate maximum total error was reached, which was setted to be 0.0001.

5. Experimental Results

The algorithm introduced above was tested on HUALI, KEYUAN, JINLING, LANJIER and SANXING electric meter images. The size of each image is 640×480. Recognition results were given in Table 1. As we can see from Table 1, the recognition rate of each electric meter is encouraged, especialy for the KEYUAN and SANXING electric meters.

Table 1. Recognition results of electric meter readings

	Number of Samples	*Correct Recognition*	*False Recognition*	*Recognition Rate*
HUALI	2600	2579	21	99.2%
JINLING	1350	1277	73	94.6%
KEYUAN	2720	2616	104	96.2%
LANJIER	1850	1741	109	94.1%
SANXING	2400	2374	26	98.9%

6. Conlusions

In this paper we have studied the problem of electric meter readings automatic location and recogntion. An efficient algorithm for meter readings location, segmentation and recognition based on BP neural network is proposed.

The location of readings is detected following a coarse-to-fine detection procedure. Then a projection-based character segmentation process is conducted to segment the readings. Finally the readings of a electirc meter is recognized using a three-layer(one-hidden layer) neural network. As a result, readings of electric meters can be located and recognized automaticly and efficiently.

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References

[1] Z. J. Zhang, Y. Li, and W. Q. Yuan, Meter character recognition method based on gray template matching, *Proceedings of the 29th Chinese Control Conference*, Beijing, China, 2010.

[2] S. T. Zhao, B. S. Li, J. S. Yuan, and G.Y. Cui, Research on remote meter automatic reading based on computer vision, *Proceedings of the IEEE Transmission and Distribution Conference & Exhibition*, 2005.

[3] R. C. Gonzalez, and R. E. Woods, *Digital image processing*, Prentice Hall, 3rd edition, 2007.

[4] R. G. Casey, and E. Lecolinet, A survey of methods and strategies in character segmentation, *IEEE Transactions on Pattern Analysis and Machine Intelligence*, 18(7), 690-706, July 1996.

[5] L. Fausett, *Fundamentals of neural networks: architectures, algorithms and applications*, Prentice-Hall, New Jersey, 1994.

[6] V. Kurkova, Kolmogorov's theorem and multilayer neural networks, *IEEE Transactions on Neural Networks*, 5(3), 501-506, 1992.

[7] Y. Hirose, K. Yamahsita, and S. Hijiya, Back-Propagation algorithm which varies the number of hidden units, *IEEE Transactions on Neural Networks*, 4(1), 61-66, 1991.